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[1] Wenyu Tang

[2*] Sisi Zhang

Exploring the role of artificial intelligence in the protection of intangible cultural heritage through short video communication

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Abstract: - The preservation of intangible cultural heritage (ICH) has gradually shifted to digital innovations in the era of expanding information technologies (IT). This study uses brief video communication to investigate the function of artificial intelligence (AI) in ICH protection. A social networking platform is connected with the AI-driven method. This study comprises instances of short videos and concentrates on essential components like musical instruments and traditional music. Next, the linguistic (text) and visual aspects of the short videos are evaluated using computer vision techniques like You only look once (YOLO) network and natural language processing (NLP) approaches. We use AI-driven analysis to find trends in the data, and we also use qualitative analysis to present it. The random forest (RF) model is developed to assess the heritage transmission level in the videos based on factors like security and cultural importance. The outcomes of the RF model are analyzed in terms of precision, accuracy, and f-measure metrics. Additionally, performance comparisons of the allocation of traditional musical instruments under different production types are carried out, and outcomes are also obtained visually using data visualization tools. This study finally shows how AI can be used to enhance ICH safety through short video communication technology.

Keywords: Intangible cultural heritage (ICH), protection, artificial intelligence (AI), musical instruments, short video communication

I. INTRODUCTION

The 20th century 50 Japan "Cultural Properties Protection Act" introduced the concept of "intangible cultural properties" for the first time [1]. The concept encompasses various traditional cultural expressions and spaces passed down through generations, including folk literature, craft technology, performing arts, and crafts, rituals, festivals, and agricultural technology [2]. Traditional music, a crucial part of traditional performing arts heritage, is an important channel for understanding Chinese traditional culture and aesthetics [3]. The protection, dissemination, and inheritance of this cultural heritage are particularly important. The concept has since gained significant attention from the international community, with the existence of a convention for the Safeguarding of ICH [4].

These include traditions and knowledge that have lasted through generations, among which are music, dancing, storytelling, and craft [5]. Such heritage is carried on over time because of the information and expertise contained by communities, rather than any physical object on display at museums. This provides a lively way of passing on these traditions through short videos communicated, for example, on social media platforms [6]. Interactive videos might be a category of dance shows, food-making tutorials, or learning artisan skills, which would mean showing the ways ICH is more accessible to wider viewership [7]. The combination of ICH with short video communication thus really has the potential ground to be turned into a powerful tool for education and conservation [8].

Short, educational videos can catch not only the essence of cultural practice but also at the same time kindle interest and inspire a person to look deeper at it [9]. Besides, this can be very helpful in preserving cultural tradition as a valuable record for posterity [10]. The objective of this research is to research the function of AI in preserving ICH through the analysis of short videos. The study intends to improve ICH preservation in modern times by using AI-driven approaches such as YOLO and NLP, as well as the RF model.

Key contribution：

1. Investigating the role of AI, particularly in the preservation of ICH through short video communication.
2. Utilizing YOLO and NLP techniques to analyze both visual and linguistic aspects of short videos.
3. Developing a RF model to assess heritage transmission levels and evaluate traditional musical instrument allocation.

[1] Xiangshan Film and Television College, Ningbo University of Finance & Economics, Ningbo, 315175, China
[2] School of Film & Television, Wuhan University of Communications, Wuhan, 430000, China
*Corresponding author: Sisi Zhang, chexvtisirgxtdoc@126.com

The organization of this work is as follows these are Section I introduces the study's focus on AI integration for ICH preservation. Section II reviews related work, and afterward Section III details the methodology. Finally, Section IV presents results and analysis, leading to conclusions in Section V.

II. RELATED WORK

Article [11] examined the use of AI technology in the preservation and sharing of ICH from a variety of angles and emphasized that, while AI can't be artistically acquired it could be replicated in a moment in history to satisfy people's needs for ICH. it was revealed in the visitor questionnaire that 66% of visitors thought that learning about the ICH firsthand was a more interested and intuitive experience technology has the potential to significantly help disseminate ICH. The study [12] examined the value of ICH resources and the state of ICH digital security both domestically and internationally. It did this by examined the trend of technological advanced permeated multiple fields from the perspectives of "user thinking" and "Internet thinking" which clarified AI, big data, and blockchain technology and analyzed the development of ICH and innovation.

Research covered the problem of how digital risks conventional methods of preserving martial arts as a cultural resource [13]. They developed an interactive system based on AI. The way it works records a martial artist's motions digitally. Users then engage in that footage, making martial arts instruction more fun and efficient. The early evaluation showed that it retrieved data faster than usual methods, showed its usefulness. the paper emphasized the possibility of AI and interactive systems in maintained and advanced martial arts history in modern times. The investigation of [14] focused on the way digital interaction influences handmade cultural heritage. Five main factors awareness, initiative, audience acceptability, technological adoption, and uncontrolled factors were shown to be significantly impacted communication. The way various components interact was explained by a suggested model. Antecedent variables were shown to be positively impacted by regulatory and situational factors.

Researchers [15] declared that a country's identity depended heavily on its cultural legacy. There were drawbacks to conventional protective strategy. The author advocated adopted contemporary digital technology such as virtual reality, activity reconstruction, and data recording to safeguard ICH in a more effective and affordable manner. The report stated that the digital technology was feasible and acceptable. Study [16] looked into how public opinion of AI affected endeavors to digitize and share cultural property. They considered both the advantages and drawbacks of that technique. While AI provided useful tools for preserved and displayed cultural material, there were worries about digital forms and the role of people in the process. They stressed the need for ethical factors and prioritized human values while creating AI for cultural heritage objectives.

The author offered Be Memories, a creative and co-created dynamic Web-App for tourists that conveys the intangible legacy of a tourist place, with material developed by destination locals [17]. Based on user-generated, engaged, and agile material, the App was able to provide local expertise, based on any findings. It allowed for the promotion of in-person visits, walking tours, and artifacts through economically feasible infrastructure while offered a level of data that was complimentary to that of documentaries, official sources, and local guide tours. Paper [18] offered the method of AI in the preservation of cultural heritage utilized virtual reality technology to achieve the digitalization of cultural heritage, recognized the safety of cultural heritage maintains pace with the trends. Due to the experiment's outcomes, virtual reality and AI were used to highlight the value of protecting cultural heritage, which enhanced its vibrancy and more accurately captured its appeal.

This "living" element of ICH was caught and expressed in a difficult manner in the article [19]. ICH was dynamic and embodied, yet the current approach frequently concentrated on physical items. They offered novel techniques for museology and data analysis that attempt to depict both the tangible and intangible, features of ICH in an interested way. They tried to improve the transmission of tangible expertized within ICH by identified gaps in existing practice. Researchers from [20] revealed an approach that uses applied AI technology to find cultural data transmitted through cultural digital image. They developed a system for the effective analysis and enrichment of a vast collection of cultural images, which encompassed all important phases and duties. The suggested technique was used and evaluated on a case study of cultural photo collections. Author [21] investigated study patterns in the ICH sector. They discovered an increased number of papers that concentrated on ICH protection. The researchers did not work together. To further the growth of ICH, the research emphasized digitization and integration with the cultural industries. The ultimate goal of the research was to develop ICH procedures that were sustainable and satisfy changed cultural demands. In-depth information on ICH was made possible by that analysis.

Article [22] stressed the adoption of IT among organization of culture. They sought to identify academically grounded allusions to IT that contribute to the protection of ICH, evaluated the degree of IT adoption by organizations of culture, and offer recommendations to cultural stakeholders for how to enhance IT adoption for

ICH protection. The analysis stated that without a proper balance of all of those factors, IT adoption as a driver of ICH safety measures remains a pipe dream for cultural influencers. The researchers of [23] identified and emphasized the need for public involvement in prevented ICH. They proposed used digital technology to develop museum material to increase public interest in discovered ICH. Digital displays on Jultagi and Daemokjang, which employed virtual reality technology, were planned with an emphasis on ICH. The objective of the work was to enhance the sustainability of global ICH for mankind through digital displays. Based on ICH, in the article [24] examined the way digital data was safeguarded and distributed. To try exploring the art of Xingyi boxing and developing a specialty in digital security, it examined the advantages of blending digital technology with imperfect martial arts technology. The research results indicated that the protective methods to enhance digital protection were proposed without any issues, and with knowledge of the state of no digital defensive culture as it currently exists.

The fashion industry's distinctive skills as craftsmen (ICH) might be protected and promoted using digital tools, according to research done by [25]. Digital devices provide solutions, even when mass production threatens cultural traditions. These technological advancements might communicate and maintain that priceless information by analyzed and archived the unique activities of artists. In conclusion, it makes the case it, in the more worldwide design business, utilized design in conjunction with digital tools might foster cultural variety and recognition.

III. METHODOLOGY

The study employed a systematic technique to examine 180 short films of traditional music, especially Ruan and Erhu instruments. The films were collected from social networking sites, organized, and assessed for relevancy and engagement. YOLO and NLP were utilized to analyze visual material. AI-powered analysis was utilized to detect trends, while qualitative analysis was employed to understand the results. To determine the amount of legacy transmission, a RF model was designed. Performance comparisons were undertaken to assess the distribution of traditional musical instruments across various production types. The technique provides a thorough approach to analyzing traditional instrumental music's ICH. Through the use of analytical instruments and videos on traditional music and ICH, the qualitative analysis for this work is incorporated into the application. Based on the Ruan and Erhu data, case studies and statistical analyses were performed. The majority of popular traditional musical instruments ICH items are outlined and clarified in this article initially. Eventually, Ruan and Erhu are chosen for several case studies based on the standard method of selection, and the outcomes should be incredible. It offers specific references for heritage project creation and distribution of digital communication goods as well as other related studies. The flow of methodologies was illustrated in Figure 1.

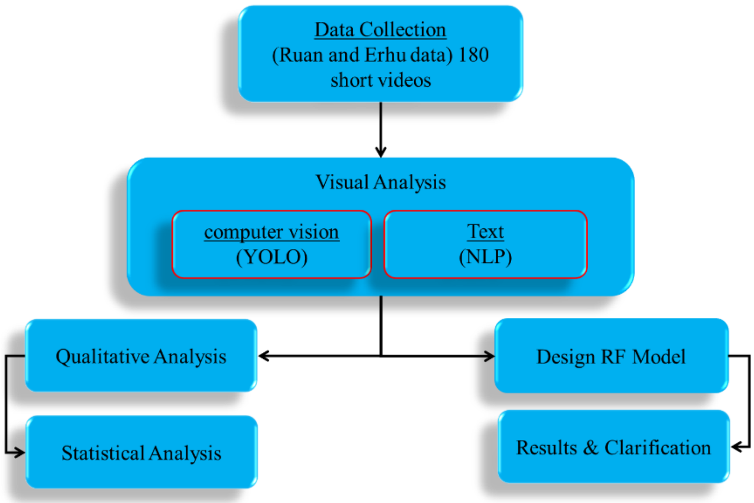

Figure 1: Methodology flow

A. Data collection and sampling

In this study, our focus is on China's traditional music, specifically Ruan and Erhu. We utilize compound nouns like "traditional music + Ruan" and "traditional music + erhu" as search keywords to gather relevant data and reviews. Through meticulous sorting, we extract single short video samples showcasing Ruan and erhu performances. A total of 180 video samples, with 90 for each instrument, are analyzed to explore the intangible cultural heritage of traditional instrumental music. By examining metrics such as likes, collections, and comments, we investigate the production models of Ruan and Erhu within the realm of traditional music heritage. This analysis is conducted using grounded theory methodology.

The paper extracts short video samples of traditional musical instruments such as ruan and erhu from the short video platform using probability sampling and summarizes their manufacturing methods. Traditional music has been named the 2021 Short Video Data Report of the Year as an important component of musical ICH initiatives. The two most common categories of ICH traditional instrumental music are Chinese ruan and erhu. Then, ruan and erhu are two types of ICH with a long history and a large number of likes, comments, and collections on the short video platform.

B. YOLO

This research analyzes the visual characteristics of brief videos using computer vision techniques such as YOLO. It's used to recognize and detect things such as musical devices and other cultural relics, allowing the study to conduct research on the digital preservation of ICH property.

The YOLO object detection approach recognizes objects in a single network pass. This detection network outperforms two-stage models in terms of detecting inference speed and tasks from start to finish. A two-phase network forecasts the class first, then the region. YOLO uses a regression model for bounding box detection and conditional probabilities for classes. As opposed to earlier research that used YOLO's basic edition for detection, our method makes use of the more quickly and precise YOLOv4 deep neural network. Its primary hub is called Darknet-53. Specifically designed for feature extraction, Darknet-53 is a fully convolutional neural network. PANet is the main component of YOLOv4. The neck is a collection of layers that stores feature maps from several stages and is located between the head and the backbone. YOLOv4 uses YOLOv3 for object detection. YOLO partitions the figure into grid cells of S by S. Bounding boxes are predicted by grid cells, and the confidence of an item is related to both the object class and the grid cell. The following kind of convolution is produced by YOLO: (S × S × Number of filters). The filter count is:

$$filters = (classes + O_d + W_{center} + Y_{center} + width + height) \times A \tag{1}$$

Where: $O_d$represents the amount of confidence that a category exists in that grid cell; however, the number of instruction classes is reflected in the variable classes. The dimensions of the box that borders with respect to the grid cell are denoted by width and height, and stands for the number of boxes that each grid cell predicts to exist. They increase the number of filters in the final YOLO layer to 18 in order to identify a single class of objects, taking into mind the following relationship among the number of classes and filters.

$$filters = (classes + 5) * 3 \tag{2}$$

Anchor boxes are the projected bounding boxes from each grid cell. The network predicts two additional coordinates $(s_w, s_z)$and the offset of the cell from the upper left corner of the figure(d_w, d_z), in addition to the anchor boxes' specified dimensions of height and width priors(o_x, o_g). Afterwards, the forecasts match.

$$a_w = \sigma(s_w) + d_w \tag{3}$$

$$a_z = \sigma(s_z) + d_z \tag{4}$$

$$a_x = o_x . f^{s_x} \tag{5}$$

$$a_g = o_g . f^{s_g} \tag{6}$$

To get relevant prior for the YOLO model, the collection of anchor boxes is grouped using k-mean clustering based on the box's boundary size. Each grid cell has an estimated risk of having an item in it. The score for class trust is also predicted by it.

$$confidence = O(bject) \times IoU \tag{7}$$

$$class_{confidence} = O(object) \times IoU \tag{8}$$

In Figure 2, IoU represents the ratio of the intersection over Union (IoU) regions of the anticipated and ground truth bounding boxes.

$$IoU = \frac{area(A_o \cap A_{hs})}{area(A_o \cup A_{hs})} \tag{9}$$

A single bounding box predicts each item. When analyzing bounding boxes for an item, non-maximum suppression (NMS) eliminates all other bounding boxes and only takes into account the one with the highest IoU.

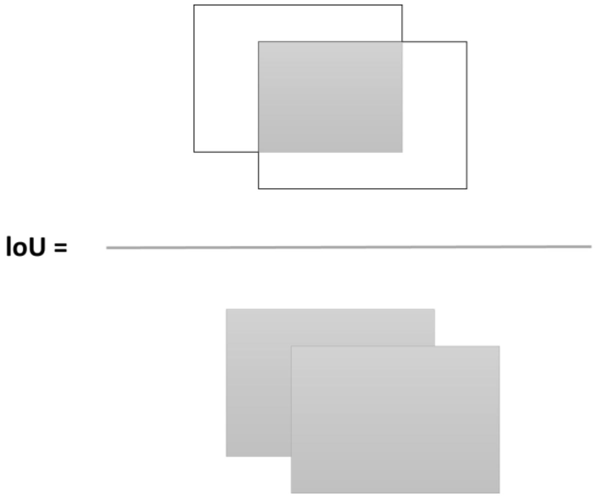

Figure 2: An example of the IoU

C. NLP

In this study, the linguistic elements of brief films are examined using NLP techniques. NLP aids in deciphering the subtitles, descriptions, and other textual material that is connected to the videos. This study helps to provide light on the attitudes, conversations, and cultural context around the ICH that is shown in the videos.

Preparing the raw source code is a crucial stage in the source analysis process. The intention is to capture the developer's semantic intent, which is thought to be included in source code identifier names, string literals, and comments. The source code contains noise, which can mislead and confound information retrieval (IR) models. Researchers typically employ NLP approaches to preprocess source code before applying IR models to the data. Figure 3 illustrates some typical preprocessing methods for raw source code. Preprocessing techniques can improve text quality and reduce noise for IR use.

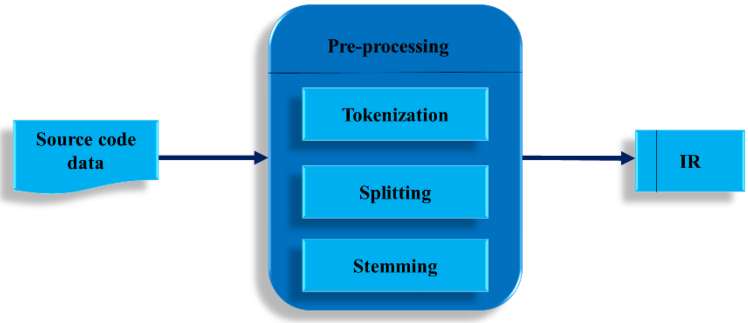

Figure 3: Normal procedure for preprocessing unstructured source code

Tokenization - Many of the terms in the source code have an impact on the program's semantics; therefore, some irrelevant and unrelated words should be eliminated and tokens should be generated from the source code text. The characters connected to the programming language's syntax (like &, →), stop words (like the), punctuation, numeric characters, and programming language keywords (like if, else, for) are eliminated in this stage.

Splitting - The form of the identifier names (TestCase) in the source code differs from regular text words. These identifier names must be divided into several sections following standard naming standards, such as capitalization changes (TESTCase), camel case (TestCase), and underscores (test case).

Stemming - Certain identifiers (e.g., its gerund counterpart localizing and localize) may be used in several forms. Currently, each word's morphological root is determined by applying word stemming.

D. NVivo Analysis

In the new media ecology, short videos are a popular form of communication. The "UGC" model, which represents User Generated Content, and the "PGC" model, which represents professionally Generated content, are the two categories into which the short video production model can be subdivided according to its internal logic. Following these two production approaches, internet users posted unique and varied remarks on the brief video content, as evidenced by the number of likes, collections, and comments, throughout the distribution of short movies featuring the intangible cultural heritage instruments of the Ruan and erhu. The percentage indicates the extent to which the audience has noticed and acknowledged the data. As a result, this article utilizes the number of likes, collections, and comments that are in excess of 1,000 as "high", the data between 100 and a 1,000 as "medium", and the data below a 100 as "low". The two genres of conventional music for instruments, Ruan and Erhu. The raw numbers of each short video are combined, and the numerical results are derived using table 1.

Table 1: Two categories of short videos with classical instrumental music that have a summary table of likes, collections, and comments.

Ruan		Erhu	
Three types of data effect display	value	Three types of data effect display	value
high+high+high	16	high+high+high	12
low+low+low	18	low+low+low	21
High + Middle + Middle	8	High + Middle + Middle	9
Medium+Medium+Low	12	Medium+Medium+Low	3
high+low+low	6	high+low+low	16
High+High+Medium	7	High+High+Medium	5
Medium+Low+Low	12	Medium+Low+Low	15
High + Medium + Low	11	High + Medium + Low	9

The two types of traditional instrumental music intangible cultural heritage production models were coded separately utilizing short video content features and release information as coding samples. First, short videos of two forms of traditional instrumental music, Ruan and erhu, were obtained by compound noun search and extensive sorting, with their creators or publishers serving as the first-level codes. The first-level coding's producer traits and the brief video content are summarized in the second-level coding. To build a third-level coding, it is finally summarized into various production modes. The results obtained are displayed in Tables 2 and 3. These Tables are compiled and compiled based on the NVivo encoding results.

Table 2: Ruan is a traditional instrument and an ICH. It is used in the production of short videos.

announcer	content	model	performance data	value
personal	Video mixing and cutting	UGC	High + High + High	5
personal	Video mixing and cutting	UGC	High + High + Medium	3
personal	Forwarding of famous works	UGC	High + Middle + Middle	2
personal	Talent show + video mixing and editing	UGC	High + Medium + Low	4
personal	Forwarding of famous works	UGC	High + Low+ Low	3
personal	Forwarding of famous works	UGC	Medium + Medium + Low	4
personal	Forwarding + talent show + video mixing and editing	UGC	Medium +Low + Low	3
personal	Forwarding + talent show + performance video + video mixing and editing	UGC	Low + Low + Low	15
Musician	Talent show	PGC	High + High + High	5
Individual + musician + performing arts company	Talent show + work forwarding	PGC	High + Middle + Middle	8
Personal + Planning/Cultural Company	Talent show + forwarding of famous works	PGC	High + Medium + Low	5
Personal + Musician	Talent show	PGC	High + Low + Low	4
Individual + musician + organization	Talent show + forwarding	PGC	Medium + Low + Low	7

Personal + musician + art company + media account	Talent show + performance (simple recording)	PGC	Low + Low + Low	6

Table 3: Erhu is a traditional instrument and an ICH. It is used in the production of short videos.

Announcer	Content	Model	Performance data	Value
personal	Video mixing and cutting	UGC	High + High + High	5
personal	Video mixing and cutting	UGC	High + High + Medium	3
personal	Forwarding of famous works	UGC	High + Middle + Middle	2
personal	Talent show + video mixing and editing	UGC	High + Medium + Low	4
personal	Forwarding of famous works	UGC	High + Low + Low	3
personal	Forwarding of famous works	UGC	Medium + Medium + Low	4
personal	Forwarding + talent show + video mixing and editing	UGC	Medium + Low + Low	3
personal	Forwarding + talent show + performance video + video mixing and editing	UGC	Low + Low + Low	15
Musician	Talent show	PGC	High + High + High	5
Individual + musician + performing arts company	Talent show + work forwarding	PGC	High + Middle + Middle	8
Personal + Planning/Cultural Company	Talent show + forwarding of famous works	PGC	High + Medium + Low	5
Personal + Musician	Talent show	PGC	High + Low + Low	4
Individual + musician + organization	Talent show + forwarding	PGC	Medium + Low + Low	7
Personal + musician + art company + media account	Talent show + performance (simple recording)	PGC	Low + Low + Low	6

E. Random Forest (RF)

In this work, the RF model is used to estimate the transmission level of legacy shown in short movies, taking into account security and cultural relevance. RF was chosen due to its capacity to handle complicated datasets, give changeable relevance measures, and assess accuracy using out-of-bag (OOB) error statistics.

The machine learning (ML) algorithm RF is based on bagging and decision trees. Classification And Regression Trees (CART) and Decision Trees (DT) are algorithms that use a succession of dividing rules to make a prediction. Nodes represent splitting rules; branches represent splitting rule decisions; and leaves reflect final predictions. At each new node generation, the data is split into two branches to form a CART until a stop requirement is satisfied. A feature and a splitting threshold are determined for each node by selecting them to minimize the variance of the data within the partitions that result from the split. The process of making a prediction involves going through the branches and nodes before arriving at a leaf. The low bias, simplicity, and interpretability of CART outweigh the advantages of RF. However, they tend to overfit the training data and are not always robust, resulting in decreased prediction accuracy.

Bagging, also known as bootstrap aggregation, was suggested as a solution to CART's drawbacks. Using numerous weak learners, like CART, bagging is an ensemble ML technique that creates a single stronger learner. A lot of poor learners are produced through bootstrapping, which is the process of sampling the entire dataset repeatedly. An average of all the predictions made by all the weak learners is used to represent the forecast. Bagging minimizes the variation of prediction errors, making the model more stable and accurate. As a weak learner, RF employs bagging and random feature selection, as well as CART. The issue with bagging is that if there are strong (dominant) features, bootstrapped samples might still be associated. By implementing random feature selection at every stage of the CART development process, this issue is lessened. It is possible to fine-tune the number of features and CARTs (where m is the number of covariates and the optimal number of features is $\sqrt{n}$ for classification and $m33$ for regression). The predictions of the RF model as a whole can be expressed as

$$\widehat{w}(t_0) = e\big(w_1(t_0), w_2(t_0), \ldots, wn(t_0)\big) \tag{10}$$

At locationt_0, the covariates are the $w_j(t_0)(j = 1, \ldots, n)$. RF includes a variable relevance measurement option that quantifies how much each feature influences the accuracy of the RF model. OOB error statistics can also be utilized to evaluate accuracy using RF. An easy expansion of RF, known as RF sp, adds buffer distance maps to every observation position as covariates. Each buffer distance map is created by computing the Euclidean distance between the centers of all prediction pixels and the center of the pixel where an observation location is located. As a result, there are exactly as many buffer distance maps in RFas observations. The random forest is represented by Algorithm 1 and figure 4.

Algorithm 1: Random Forest (RF)

```
importnumpy as np
class Decision Tree:
def __init__(self):
self.tree = None
def fit(self, X, y):
pass
def predict(self, X):
pass
class Random Forest:
def__init__(self, n_estimators = 100, max_features = 'sqrt'):
self.n_estimators = n_estimators
self.max_features = max_features
self.trees = []
def fit(self, X, y):
for _ in range(self.n_estimators):
bootstrap_indices = np.random.choice(len(X), len(X), replace = True)
X_bootstrap = X[bootstrap_indices]
y_bootstrap = y[bootstrap_indices]
if self.max_features == 'sqrt':
n_features = int(np.sqrt(X.shape[1]))
elif self.max_features == 'log2':
n_features = int(np.log2(X.shape[1]))
else:
n_features = X.shape[1]
feature_indices = np.random.choice(X.shape[1], n_features, replace = False)
X_subset = X_bootstrap[:, feature_indices]
tree = DecisionTree()
tree.fit(X_subset, y_bootstrap)
self.trees.append(tree)
def predict(self, X):
predictions = np.zeros((X.shape[0], len(self.trees)))
for i, tree in enumerate(self.trees):
predictions[:, i] = tree.predict(X)
return np.mean(predictions, axis = 1)
X_train = np.array([[...], [...], ...])
y_train = np.array([..., ..., ...])
rf = RandomForest()
rf.fit(X_train, y_train)
X_test = np.array([[...], [...], ...])
predictions = rf.predict(X_test)
```

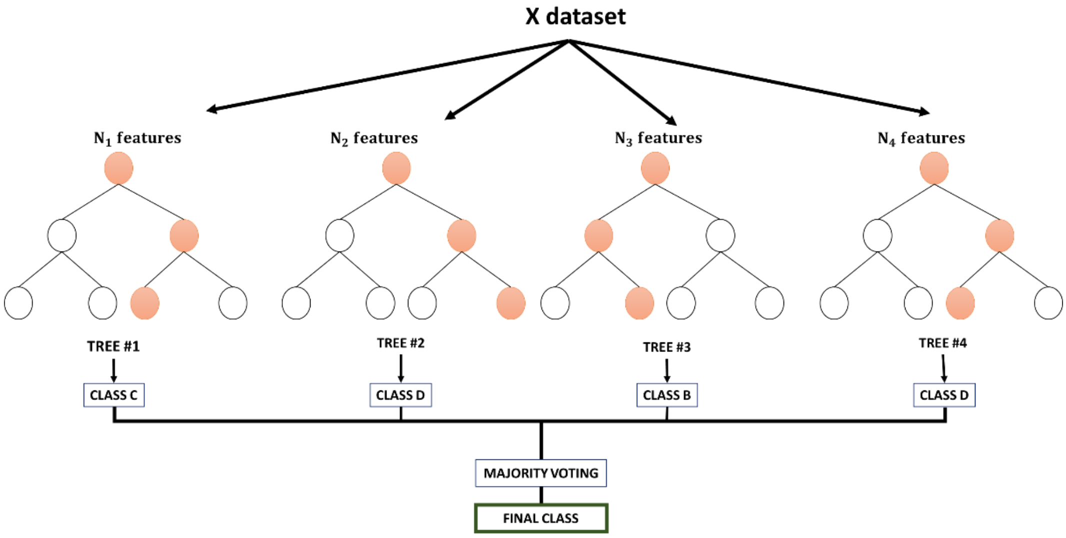

Figure 4: Illustration of the RF method.

IV. Result and Analysis

Examination of two traditional instrumental music genres' production strategies and communication impacts on short videos. The term UGC initially originated in the fields of internet publishing and new media publishing. Generally, refers to a production approach where the primary source of output is regular people. Professional institutions do not support this production approach, and there is no technical assistance. Essentially, individuals create material on their own and distribute it to appropriate venues. PGC refers to professionally generated content. In comparison to UGC, the publishing subject has advanced professional talents and technical equipment, as well as relatively high content quality.

A. Analysis of the short video about Ruan's ICH and its distribution impact

Ruan ICH's short video has expanded its dissemination and captivated the audience's admiration and pride in the Ruan culture. The production model of the Ruan video includes UGC and PGC. UGC videos account for 54% of the total parameters, while PGC videos account for 46%. The audience's psychological changes during the viewing process of the Ruan videos are reflected in the comment content. UGC videos are mostly reflected in content likes, love, and roses, while PGC videos have more in-depth expressions, such as "popping up the joys and sorrows of life" and "searching for music." The most direct effect is the audience's forwarding behavior, while the cognitive effects are not significant. Overall, the Ruan video effectively affects the audience's concept and value system, enhancing their appreciation for Ruan culture.

The Ruan ICH short video (UGC): UGC production model analysis focuses on individual publishers publishing content related to Ruan, personal talent shows, forwarding of famous works, and short performance videos. The effect data under this production model is widely distributed in eight situations, with high numerical expressions achieved through mixed short videos, reposting of works by famous artists, and high-quality personal works. Compared to Erhu ICH short video effect data parameters, Ruan has a relatively large proportion of parameters in the three-effect data, with half of the total parameters being close to UGC.

The Ruan ICH short video (PGC): The PGC production model involves individuals and musicians, with institutions like performing arts companies, cultural companies, planning companies, educational institutions, art companies, and official media accounts involved. The content of published works focuses on personal work display, TV program forwarding, famous artist's works forwarding, and performances. The effect data for PGC is concentrated in six situations, with a low number of likes, collections, and comments. Compared to the Erhu ICH short video PGC production model, the Ruan ICH short video has a lower number of likes, collections, and comments.

B. Analysis of the short video about Erhu's ICH and its distribution impact

Digital media has significantly expanded the influence of Erhu's ICH short videos, allowing them to stimulate emotional resonance and spread quickly. Traditional instrumental music Erhu ICH short video production model can be divided into UGC and PGC. The latter has a larger proportion of positive emotions and emotional changes in the audience, demonstrating the communication effect. Psychological comments on Erhu ICH short videos in production mode are more specific than likes and flowers, expressing more specific emotions and emotional changes. Compared to Ruan ICH short videos, PGC, the Erhu ICH short video in production mode has a certain level of recognition.

The Erhu ICH short video (UGC): UGC production model analysis focuses on publishing content mainly involving Erhu-related mixed-cut short videos, personal talent shows, and forwarding of famous works and folk performances. Personal talent shows and folk performances are mostly non-professional, simple self-made short videos. Performance data from the production mode shows that traditional instrumental Erhu ICH short videos have high, medium, and low-performance data in terms of likes, collections, and comments. Combining published content and performance data allows for higher-performance data by mixing short videos and reposting famous works, while simple personal presentations and performance videos present lower values.

The Erhu ICH short video (PGC): PGC production model analysis reveals a more diverse distribution of publisher roles, with individuals with specific skills, musicians, media official accounts, performing arts companies, and piano stores as main publishers. The content includes high-level personal presentations, program clips, performance videos, and work presentations by students and actors. The model has achieved a high number of likes, collections, and comments, with four effect data types. While the overall value is relatively high, relatively simple short video production has a relatively low number of likes and comments.

C. Evaluation of the impact of dissemination for the brief video Ruan and Erhu ICH

As a result, there are two types of material: UGC and PGC. Whether the publication subjects have recording technology or comparatively professional knowledge and abilities divide them, based on Tables 2 and 3.

Traditional instrumental short videos, predominantly produced using UGC, account for 54% of both musical objects in the sample. PGC, with 46% of the total, is also significant, with short video musicians and institutions involved. Despite this, traditional short videos continue to be produced using this method. Short videos produced using PGC modes are more likely to receive high numbers of likes, collections, and comments. Despite the distribution of effect data, PGC mode has a higher number of high-effect data parameters, affecting the communication effect and driving action-level effects. Tables 2 and 3 show published content of high + high + high and high + high + medium, mostly based on music and scenery. However, these short videos have serious homogenization and pan-entertainment problems, hindering the dissemination of ICH content.

The study focuses on the personal talent displayed in short videos of traditional musical instruments, Ruan and Erhu. These videos showcase professional performances, enhancing the aesthetic experience for the audience. The dissemination effect awakens psychological impact and forms an action-level effect, thereby conveying the artistic and cultural value of this ICH content. This approach helps the audience understand the cultural value of these instruments as ICH. Homemade short videos, regardless of production mode (UGC or PGC), often have low-value distribution due to production quality issues, indicating that even with professional knowledge, these videos cannot achieve good communication effects. The production model for Ruan and Erhu's short videos does not guarantee the original taste of their music, but it can better display national cultural genes and lay the foundation for inheritance. The model’s content can better display national cultural genes and promote the dissemination of traditional music and intangible cultural heritage. This will meet users’ needs for knowledge and traceability, build a true understanding of ICH, and inspire action-level feedback. Encouraging intangible cultural heritage protection units at all levels to promote modern technology in the protection, inheritance, and dissemination of ICH is also necessary.

In this study, researchers conducted multiple experiments to evaluate the performance of ML classifier models on diverse datasets. Our methodology was implemented using Python (version 3.10) on a Windows 11 operating system. The computational setup for this study includes an AMD Radeon RX 6700 XT graphics card, an AMD Ryzen 9 processor (5000 series), and 32GB of RAM. The effectiveness of the suggested method RF was analyzed by applying a set of parameters including precision, recall, sensitivity, and specificity are compared with existing methods are Forest by Penalizing Attributes (Forest PA) [26], Averaged One Dependence Estimators (AODE) [26], K-Nearest Neighbor Rough Sets and analogy-based reasoning (RSeslibKnn) [26].

Accuracy Loss: Figure 5 displays the performance of our RF method relative to the baseline. It depicts how the accuracy of our model changes with each parameter fixed, reduced, or altered. This graph gives a clear idea about how various effects on the accuracy of the RF model. This is the best way to see the robustness and versatility of the RF model for the classification.

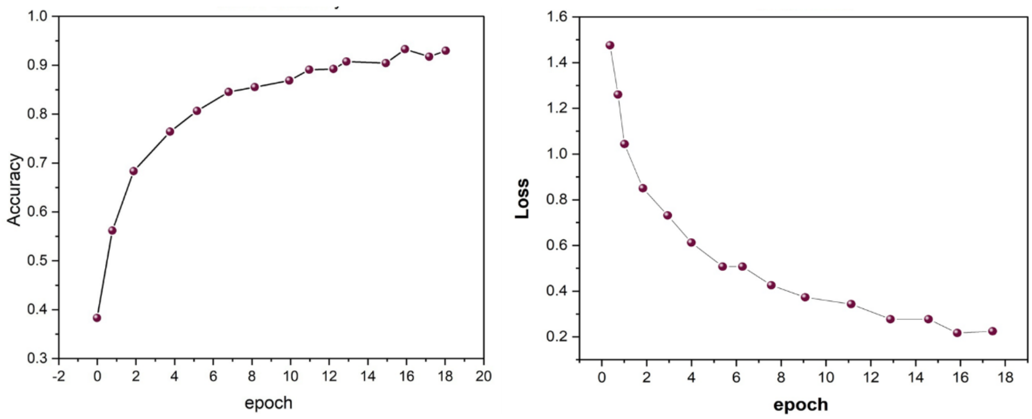

Figure 5: Result of Accuracy Loss

Precision: Precision evaluation is important to discuss the effectiveness of our RF approach in this study. In this regard, the precision contributes to determining the ability of the model against false positives by taking all the positive cases and calculating the ratio of true positive predictions. Formula: It is computed using.

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

Here, FP is for false positives and TP is for true positives. We compared our method with state-of-the-art techniques like RSeslibKnn, Forest PA, and AODE. Precision is based on the Precision chart and represented in Figure 6 and Table 4. The high Precision of our proposed method RF outperforms all other methods; thus, it had an impressive score of 90.5%.

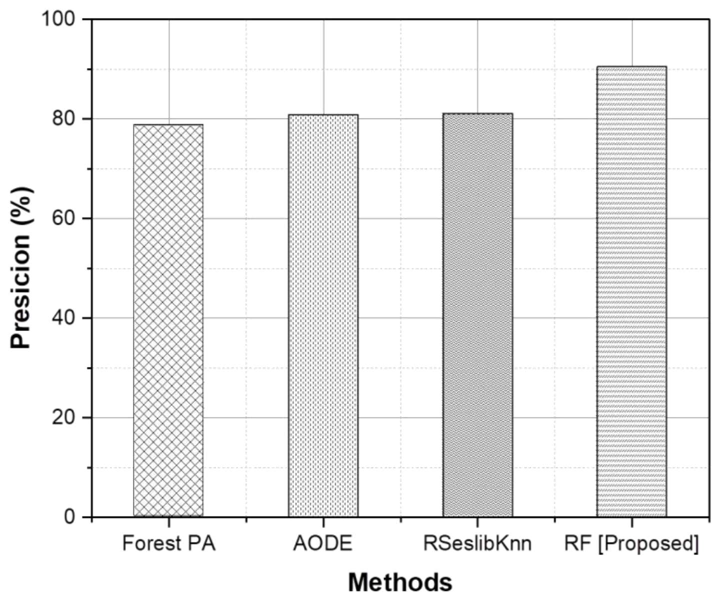

Figure 6: Comparison of Precision

Recall: Recall concerns the RF technique and deals with the question of how many of the actual positive events we were able to capture. In the case of any positive event, recall is the ratio of actual positive predictions over all possible real positive cases. It is a measure used to show if indeed a model can be able to capture all the actual positive cases. It is calculated as follows:

$$Recall = \frac{TP}{TP + FP} \tag{12}$$

TP is true positive, and FN is false negative. To compare, we evaluate it with some of the state-of-the-art techniques such as RSeslibKnn, Forest PA, and AODE. This is given as a recall chart in Figure 7 and Table 4. In the context of recall, our proposed method RF can beat all other methods, scoring as high as 93.4%.

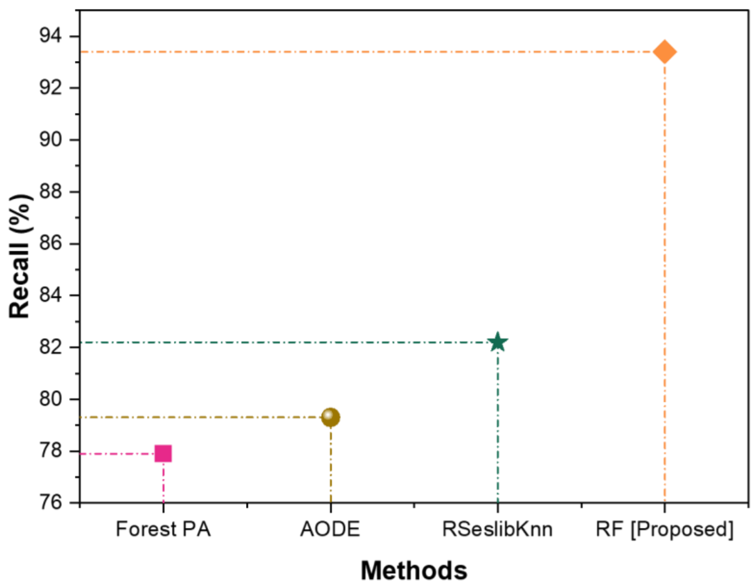

Figure 7: Comparison of Recall

F-measure: The F-measure may be used for the evaluation of the overall performance of making predictions by a classification model. The statistic means the equal value of precision and recall; that is, it is the harmonic mean of precision and recall.

$$F - measure = 2 \times \frac{(precision \times recall)}{(precision|recall)} \quad (13)$$

Our proposed RF method is compared thoroughly with other approaches, such as Forest PA, AODE, and RseslibKnn, and from which we have analyzed the F-measure in our study. The recall chart in Figure 8 and Table 4 shows that our proposed method RF outperforms all the other methods in terms of F-measure, with an impressive 95.4% score.

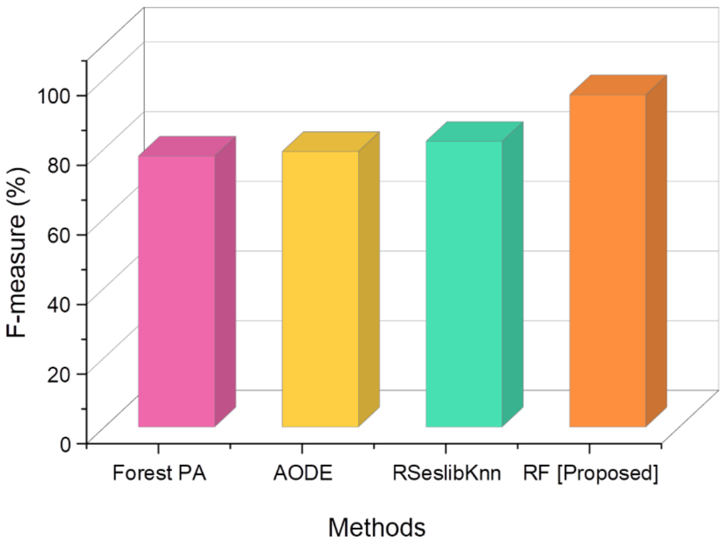

Figure 8: Comparison of F-measure

Table 4: Comparison Parameters

Methods	F-measure	Recall	Precision
Forest PA	77.8	77.9	78.7
AODE	79.1	79.3	80.8
RSeslibKnn	82	82.2	81.1
RF [Proposed]	95.4	93.4	90.5

V. Conclusion

This study demonstrates the potential of AI and digital innovations in preserving ICH through short video communication. By integrating AI-driven methods with social networking platforms, we have effectively analyzed and evaluated various aspects of ICH, focusing on musical instruments and traditional music. Our use of computer vision techniques and NLP approaches has enabled us to uncover trends and patterns within the data, while qualitative analysis has provided deeper insights. The development of the RF model has facilitated the assessment of heritage transmission levels, considering factors such as security and cultural importance, with high precision and accuracy. This article analyzes data on two popular short videos of traditional instrumental music on the short video platform. The study identifies UGC and PGC as the primary production models for ICH short videos, with UGC content being less suitable due to its entertainment and historical value, while PGC content, supported by ICH inheritors, showcases its original characteristics. Experimental findings values such as precision (90.5%), recall (93.4%), and f-measure (95.4%) were all found to be best achieved by the suggested RF method.

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